NBER WORKING PAPER SERIES

TO BE OR NOT TO BE INNOVATIVE: AN EXERCISE IN MEASUREMENT

Jacques Mairesse
Pierre Mohnen

Working Paper 8644
http://www.nber.org/papers/w8644

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2001

To Be or Not To Be Innovative: An Exercise in Measurement
Jacques Mairesse and Pierre Mohnen
NBER Working Paper No. 8644
December 2001
JEL No. C35, L60, O31, O33

ABSTRACT

In this paper, we put forward the idea of an innovation accounting framework and consider two main indicators based on it: expected innovation and innovativeness. The framework is the analogue of the standard framework of economic growth accounting, with innovativeness being a parallel notion to that of (total factor) productivity. We provide an illustration of the idea using data from the European Community Innovation Surveys (CIS1 and CIS2) and measuring innovation by the share of firm innovative sales. We adopt a generalized tobit model of the propensity and intensity of innovation as our accounting framework. We first apply the framework to a comparison of the innovation performance of French manufacturing industries, while also checking the robustness of our estimates to the use of micro-aggregated firm data provided by Eurostat *versus* the original individual firm data. We also provide an overview of the results of a larger comparison of innovation across seven European countries.

Jacques Mairesse
CREST-INSEE
15, boulevard Gabriel Peri
92244 Malakoff cedex, France
and NBER
mairesse@ensae.fr

Pierre Mohnen
MERIT
Maastricht University
P.O. Box 616
6200 MD Maastricht, Netherlands
p.mohnen@merit.unimaas.nl

I. INTRODUCTION

Out of a growing concern that inputs into the innovation process were insufficiently covered by the notion of R&D expenditures as defined in the *Frascati Manual* (OECD, 1963), that the output of that process had to be measured in a more direct way than through patents, and, last but not least, that information was lacking on the organisation of research and innovation activities, statistical experts met under the auspices of the OECD to set guidelines for the design of innovation surveys. These have been formulated in the so-called *Oslo Manual* (OECD, 1992; OECD and Eurostat, 1997).

To date, a number of countries have launched two or three innovation surveys, which have been conducted in more or less the same fashion, following the guidelines set out in the *Oslo Manual.* In Europe, these surveys are known as CIS (Community Innovation Surveys). Despite efforts by Eurostat towards harmonisation, the first round of surveys, CIS1, performed in 1993 and relating to 1990-92, suffered from major differences in terms of coverage, sampling, questions asked, reporting unit, and organisation of the survey (see Archibuggi *et al.*, 1994, for details). The second round of surveys CIS2, performed in 1997 and pertaining to the period 1994-96, was more comparable across countries, and the third round of surveys, CIS3, which is currently under way, is expected to show considerable improvements. In addition to exploitation of the results by national statistical agencies, Eurostat assembles and analyses the country data in a consistent way in an effort to render them, to the fullest extent possible, suitable for international comparisons. Eurostat also contributes to making the CIS data available to researchers for further investigation. However, in order to strictly preserve the confidentiality of firm-level information, Eurostat delivers the data in micro-aggregated form.[1] The micro-aggregation process adopted by Eurostat for CIS1 and CIS2 consists of replacing each observation of a given variable by an average of itself and the two adjacent observations in a ranking order of the observations for that variable.[2]

To compare innovation performance across industries or countries we have elsewhere proposed two related indicators (Mohnen and Dagenais, 2001; Mohnen, Mairesse and Dagenais, 2001). Both use information retrieved from the innovation surveys. The first is the expected share of innovative sales in total turnover. It estimates the percentage of innovative sales that can be expected for a firm, an industry or a country, when controlling for a number of explanatory variables that influence innovation. The second is what we call innovativeness, which is defined as the difference between the observed and the expected share of innovative sales. In a model or framework which aims to account for innovation, innovativeness can be viewed as an analogue to total factor or multifactor productivity in the standard production (or output growth) accounting framework.

In this article, we do two things. We first illustrate the construction and interpretation of the two proposed innovation indicators, while checking how robust they are to the use of micro-aggregated *vs.* individual firm data. To do so, we contrast the estimation results obtained on two random samples of French firms, both drawn from CIS2. One is drawn from the raw data set, the other one from the micro-aggregated data set. We then further illustrate the use of the two indicators by comparing innovation across seven European countries on the basis of the CIS1 micro-aggregated data for these countries.

The article is organised as follows. In Section II, we define the two analytical innovation indicators as they can be constructed from an appropriate econometric analysis of the available innovation survey data. In Section III, we examine to what extent these two indicators may be sensitive to the micro-aggregation of the individual data, putting them to test in a comparison of innovation across French manufacturing industries based on the French CIS2 survey. In Section IV, we proceed to an international comparison of innovation across seven European countries using CIS1 data. In Section V, we conclude by discussing how the two analytical indicators compare to other innovation metrics and by suggesting possible avenues of future research to refine our measure and understanding of innovation.

II. INNOVATION INDICATORS FROM INNOVATION SURVEY DATA

Innovation surveys based on the guidelines of the *Oslo Manual*, such as the CIS surveys, typically provide information on the input and output of a firm's innovative activities, as well as on the modalities of these activities. On the input side, we have quantitative data on R&D expenditures and other current and capital expenditures on innovation, and know whether firms engage or not in R&D, in R&D collaboration or in the outside acquisition of technology. On the output side, we know whether or not firms have introduced new products or processes, and have quantitative estimates on the share of sales broken down into unchanged or marginally modified products, and significantly improved or entirely new products, the share in sales of new or improved products not only new to the firm but also to its market. Regarding the modalities of innovation, we know whether R&D was performed continuously or not, and can obtain qualitative information on sources of knowledge, reasons for innovating, perceived obstacles to innovation and perceived strengths and weaknesses of various appropriability mechanisms.

In this work, as in other related work, we assess the extent of innovation in a given industry or country by the share of innovative sales. Innovative sales can be viewed as a sales weighted measure of the number of innovations. Compared to R&D expenditures – and even to the broader concept of innovation expenditures defined in the *Oslo Manual*, which embraces expenditures such as pilot studies and market analyses – innovative sales have the advantage of being an output measure of innovation. Also, in contrast to patents, they have a much broader scope and are defined in a more straightforward way than through the decisions of the innovating firms to protect their intellectual property rights.[3] Innovative sales, as we define them here, are constructed on the basis of the CIS1 and CIS2 questionnaires, as the sales due to new or improved products for the firm (but not necessarily for the market) in the last three years (1990-92 for CIS1 and 1994-96 for CIS2).[4]

In assessing the extent of innovation in a country or an industry by the share of innovative sales, we believe that an important first step in an inter-country or -industry comparison, irrespective of more focused and deeper analyses, is to control for differences in industry composition, average firm size, as well as average intensity firm R&D effort, and possibly characteristics of the economic environment. This implies the explicit choice of an econometric model, or to use a different vocabulary, an (econometrically based) “accounting framework”, whose implementation would be, of course, largely dependent on the available information.

In particular, we consider it important to base a country or industry comparison not just on the innovative sales of innovating firms but also on the propensity of firms to innovate or not. If we restrict the analysis to innovating firms only, we ignore the information about the non-innovating firms, and as a matter of fact our analysis would be conditional on that restriction, or otherwise would be likely to suffer from selection biases if we wanted to extend its results to the whole population of firms. If we limit ourselves to qualitative information on whether or not firms are innovative (responding yes or no to the question of to whether or not they had introduced any new or improved products or processes in the last three years), we can compute an index of ability or propensity to innovate for all firms, but we then fail to exploit the quantitative information that we have on innovating firms but that we do not have for non innovating ones.[5] Therefore, we surmise that the appropriate way to proceed is to combine both types of information by implementing an appropriate econometric model or accounting framework which tries to account for the fact that firms are either innovative or not, and, for those that are innovative, the extent to which they are so.[6] In what follows, we thus focus on a generalised tobit model, which seems to be the natural two equations specification to consider (Mohnen and Dagenais, 2001; Mohnen, Mairesse and Dagenais, 2001).

As an important outcome of such accounting framework, we propose to focus on two types of innovation indicators: "expected innovation" and "innovativeness". The expected (or explained) innovation indicator is the share of innovative sales which can be predicted given the model adopted to account for both the propensity to innovate and the intensity of innovation, for a given set of values of the exogenous variables in this model. It measures the share of innovative sales that we would predict for firms in a particular industry, of a given size and given intensity of R&D effort, in a certain economic environment, and so on.

Innovativeness is the unexpected (or unexplained or residual) part of the actual observed share of innovative sales, which remains unaccounted for by the model as it stands.

The interest of the expected innovation indicator (and the underlying accounting framework) is that it goes beyond merely reporting the observed share of innovative sales, and attempts to explicitly assess the differences which are imputable to the differences in industry, size, R&D effort, economic environment, and so on. It should allow for a better-informed comparison of innovation performances across different countries, industries or group of firms; and different time periods.[7]

Innovativeness is to innovation what multifactor productivity or total factor productivity (TFP) is to output. The measure of innovativeness is conditional on a model of the "innovation function" and a set of innovation factors, just as TFP is conditional on an explicit or implicit specification of the production function and measured factors of production.[8] Innovativeness is the "residual" of the innovation function, just as TFP is that of the production function. Both thus correspond to omitted factors of performance such as technological, organisational, cultural or environmental factors, although TFP is commonly interpreted as an indicator of technology. However, both also correspond to other sources of misspecifications and errors in the underlying model of the innovation or production function, and could be rightly viewed as "measures of our ignorance". Both innovativeness and TFP can, in principle, be measured in terms of growth and levels, and for intertemporal comparisons (between time periods) as well as for interspatial comparisons (across countries, industries or firms). In this article, however, we shall estimate and compare levels of industry or country innovativeness, whereas TFP is usually considered and measured as TFP growth.[9]

Innovativeness could ideally acquire, in the context of innovation comparisons, a usefulness that would be similar to, if not on a par with, that acquired by TFP over the years in the context of productivity comparisons. However it remains, in the case of innovativeness as in that of TFP, that these are not simple indicators, but elaborate constructs, and that their meaning and usefulness ultimately rely on the consideration of the entire underlying accounting framework from which they arise.

III. INNOVATION INDICATORS FOR FRENCH MANUFACTURING BASED ON CIS2 DATA: ROBUSTNESS TO MICRO-AGGREGATION AND COMPARISON ACROSS INDUSTRIES

To illustrate the construction of the proposed expected innovation and innovativeness indicators and, at the same time, examine their robustness to the micro-aggregation procedure used by Eurostat to protect statistical confidentiality, we estimate our generalised tobit model, using the raw and micro-aggregated French CIS2 data. The raw data are those collected by SESSI (Service des Statistiques Industrielles) of the French Ministry of Industry. The micro-aggregated data are those provided by Eurostat. The industries to which the firms belong are defined using the NACE 1 (Rev. 2) classification. In order to have a sufficient number of observations per cross-sectional unit, industries are grouped into ten sectors, following Eurostat's (1997) presentation of descriptive statistics from CIS1 (see Annex for the NACE codes corresponding to these sectors).[10]

To make the SESSI data comparable to those from Eurostat, the nominal data from SESSI are converted to euros, divided by the raising factor, and codified in the same way as Eurostat data, *e.g.* as missing data for all variables corresponding to questions that needed be answered by innovators only. Both data sets are cleaned for outliers. Firms with more than 100 000 or less than 20 employees were eliminated, as were those with an R&D/sales ratio of over 50%. From each of the two data sets, we take a random sample of 1 000 firms in the high-R&D sectors (regrouping chemicals, machinery and equipment, electrical machinery and transportation equipment), and a random sample of 1 000 firms in the low-R&D sectors (regrouping textiles, wood, rubber and plastics, non-metallic mineral products, basic and fabricated metals, and furniture and not-elsewhere-classified industries). As a first rough control for industry heterogeneity, we estimate separately our model from the samples in the high-R&D and the low-R&D sectors, based on previous econometric evidence showing large differences not only in R&D intensity but also in the returns to R&D between these two groups of sectors (Griliches and Mairesse, 1984). Note that to control further for industry heterogeneity, we also introduce industry dummies in each of the two equations of the generalised tobit model (four in the high-R&D sector samples; six in the low-R&D sector samples).

The first equation of our tobit model explains the ability or propensity to innovate. Are considered as innovators, those enterprises that declare having introduced a technologically new or improved product or process, or having unsuccessful or not yet completed projects to introduce such a product or process in 1994-96. The second equation explains the intensity of innovation (if a firm innovates). The intensity of innovation is captured by the share in sales of innovative products, defined as technologically new or improved products introduced between 1994 and 1996.[11] The explanatory variables introduced in the first equation to explain the ability to innovate are, in addition to the industry dummies, the fact of being part of an enterprise group, and size, measured by the number of employees (in logarithm). For the intensity of innovation we have, in addition to the preceding explanatory variables, an indicator for the strength of competition, an indicator for the proximity to basic research, the existence of any kind of co-operation in innovation, the absence of any R&D activity, the existence of continuous R&D activity, and the R&D intensity. Competition is deemed to be strong when opening new markets or increasing market share gets the highest mark, *i.e.* three. Proximity to basic research is given the value of one when sources of information from universities/higher education or government laboratories have a score of two or three. Firms conducting both transitory and permanent R&D are classified among the continuous R&D performers.

An ideal test of the robustness to micro-aggregation of the estimates would have been to contrast the results obtained from the same firms once with raw data and once with micro-aggregated data. Instead, we picked two random samples from both data sets for each of two sub-samples, high-R&D sectors and low-R&D sectors and contrast our results for these random samples. In a sense, this is a more demanding (and more realistic) test since the individual and "micro-aggregated" firms in the corresponding samples are not necessarily the same, but are randomly drawn from the same population of firms, in the high-R&D and low-R&D sectors respectively.

Before comparing the estimates of our model, it is instructive to compare the descriptive statistics on the individual and micro-aggregated data samples. This is done in Table 1 and Figures 1 and 2. As is evident from Table 1, the sample means of the different variables entering in our model are very close in the two types of samples. First, the sample distribution with respect to the industrial composition is very similar. Only for textiles does the share of firms in the two samples differ by more than two percentage points. For all the other variables (other than the industry dummies), we report the sample means and the sample standard deviations. We also give the standard error for the test of comparison of the sample means for the two types of sample.[12] A difference between the sample means of a variable in the two types of sample is statistically significant (at the 5% confidence level) if it exceeds roughly two times the corresponding standard error for the test. An asterisk marks these cases. In the case of the high-R&D sector samples, we find significant differences among the two types of samples only for the percentage of R&D-performing firms among the innovators and, among those, for the share of continuous R&D performers. In the low-R&D sector samples, we find significant differences for the share in sales of innovative products, the percentage of R&D performers, the percentage of continuous R&D performers, the R&D/sales ratio, and the percentage of firms close to basic research. However, even in these cases, the differences are not very large. We also note that differences between the sample standard deviations for the individual and micro-aggregated data samples are quite small. In fact, the differences of the means of all the variables are much greater and statistically significant between the high-R&D and the low-R&D sector samples (which is consistent with our choice to consider them separately in estimating our model). Firms in the high-R&D sectors are larger, more innovative (in frequency and in size), and more R&D-intensive. They also collaborate more in innovation, face more competition, are closer to basic research, and more often belong to an enterprise group.

In Figures 1 and 2, we present the decile distribution of the share in sales of innovative products in the four samples. Again, it is clear that, by and large, the distributions are very close for the micro-aggregated and individual data samples, and the distributions show greater differences between the low-R&D and high-R&D sector samples (although in both cases, the bulk of the firms have a relatively low share of innovative sales).

In Table 2, we present the estimation results of the generalised tobit model that underlies the constructed indicators of innovation. We experienced difficulties in estimating the correlation coefficient ρ between the error terms in the two equations of the model. A grid search revealed that the highest likelihood was obtained at values of ρ tending towards one, and we therefore decided to settle for a value of 0.95.[13]

We can see first that the estimates are rather similar whether we take the individual or the micro-aggregated data. If we leave aside the industry dummies, there is only one occurrence of a significant coefficient in one sample and not in the other for the high-R&D sectors, and four occurrences for the low-R&D sectors. Actually, the confidence intervals of the estimates always overlap, except for the wood industry dummy. The two types of data thus do not seem to yield systematically different estimates, even in such a non-linear model as our tobit model. These results confirm and reinforce the conclusion already drawn for CIS1 by Hu and DeBresson (1998) that the use of micro-aggregated data produces reliable results. However, it should be noted that our model does not perform very well, and, hence, the lack of significant differences between the two sets of estimates could very well be due in part to their poor precision.

Table 2 also reveals clearly that the model performs somewhat better in the high-R&D than in the low-R&D sectors. Firm size, R&D intensity and the characteristic of conducting continuous R&D are strong explanatory factors of innovation for the high-R&D sectors. The same can be said for firm size, for being part of a group or being an R&D performer, or for the strength of competition in the case of the low-R&D sectors but, surprisingly, R&D intensity does not appear to be significant.

In Table 3, we present the results of applying our innovation accounting framework to the comparison of the innovation performance of the industries in the high-R&D and low-R&D sector samples, as estimated respectively on the individual data (in the two upper panels) and on the micro-aggregated data (in the two lower panels). We account for the observed innovation intensity in terms of the innovation intensity expected (explained by the underlying model) and innovativeness (unexplained by the model). We also decompose the expected intensity into an overall average intensity and three categories of "structural" effects corresponding to the explanatory variables introduced in our model: size and group effects, R&D effects, and environment effects (perceived competition and proximity to basic research). For each industry in a given sample, we start (column 1) from the overall average of observed innovation intensity for the full sample (*i.e.* a weighted average of the different industry averages). Note that this average is defined over all firms in the sample, irrespective of whether they are innovating or not, taking observed intensity of innovation to be zero for non-innovating firms. We then compute the expected intensity of innovation for each industry by taking a linear approximation of the expected intensity of innovation around the overall observed averages of the different variables in the model. The different terms of this decomposition are thus approximate measures of the respective contributions of the variables to the expected intensity in each industry. By taking a linear approximation, we ensure that these measures are independent of the sequential order of the variables in the decomposition. The "average" row in each panel of Table 3 makes it clear that this decomposition is to be interpreted in terms of industry effects relative to full sample effects (industry deviations to full sample effects). It also makes clear that innovativeness, computed as the difference between the observed and expected average innovation intensity in each industry, is to be viewed as industry innovativeness relative to overall innovativeness.[14] When weighted appropriately by the different number of observations in each industry in the full sample, the three categories of effects and innovativeness (shown in the "industry" rows in each panel) average out to zero.

If we take, for example, the vehicles industry in the case of the individual data sample (first row of first panel), we see that the average observed innovation intensity in this industry is 24%; that is 2.7% higher than the 21.3% average observed intensity for all firms operating in the high-R&D sectors. This difference (2.7%) is accounted for by the sum of structural effects of 3.7% and the relative innovativeness of -1%, the former being mainly due to the combined effect of size and group-participation (3.6%) and to a tiny extent to the combined effect of all R&D variables (0.1%).

If we compare the innovation performance in the vehicles and machinery and equipment industries, we see that according to our estimates the vehicles industry has a clear size/group advantage as well as an R&D advantage, both types of effects explaining a difference in expected innovation intensity of 6.7% between the two industries. Actually the difference in the observed innovation intensity is significantly smaller, of 3.5%, since innovativeness is higher in the machinery and equipment industry (2.2% compared with –1%).

As a general observation, it appears that most of the inter-industry differences in expected innovation intensity are due to the size/group effect, and that the sum of structural effects and innovativeness vary roughly in about the same range from 0% to about + or –3% (with the exception of the chemicals industry and the non elsewhere classified products industry where innovativeness exceeds + or –6%). In fact, the inter-industry differences in the observed innovation intensity tend to be themselves relatively limited, in the range of 0 to + or -8% within the high-R&D and low-R&D sectors(while much wider across the two type of sectors).

Figures 3 and 4 permit an easy industry by industry comparison of the differences in innovativeness and the sum of "structural effects", as estimated on the individual and the micro-aggregated data. By and large, the figures confirm that it does not matter much whether we work with micro-aggregated data or with individual data. Only for innovativeness in the vehicles industry do we see a sizeable difference, with a change in the sign.

IV. COMPARISON OF INNOVATION INDICATORS BETWEEN SEVEN EUROPEAN COUNTRIES BASED ON CIS1 DATA

To further illustrate the construction of our expected innovation and innovativeness indicators, and our innovation accounting framework, we now turn to an international comparison of innovation. In Mohnen, Mairesse and Dagenais (2001), we estimated a generalised tobit model on the pooled CIS1 micro-aggregated data of the manufacturing sectors of seven European countries: Belgium, Denmark, France, Germany, Ireland, the

Netherlands, Norway and Italy. Compared to section III, we now distinguish eleven industries, adding the food sector for which data were unavailable for France in CIS2 (see the Annex for the corresponding NACE codes). Again, we estimated the model separately for high-R&D and low-R&D sector samples. In pooling all observations, we estimated a common structure that was applied to individual country data in order to compare their innovation performance.

We defined an innovating firm as one that reports positive values of innovative sales. Indeed, some firms declare having introduced a new product or process and yet report no innovative sales. We treated such firms as non-innovative.[15] As explanatory variables, we have basically the same variables as in the preceding model applied to French CIS2 data, with a few minor differences. We now have not only industry but also country dummies to control for heterogeneity. The two continuous variables, size (the number of employees in logarithm) and R&D intensity, are expressed in deviations from the average of country averages, *i.e.* in deviation from a hypothetical Europe where each country has equal weight. Co-operation relates to R&D only. Competition is deemed to be strong when increasing or maintaining market share receives a rating greater than or equal to four, and proximity to basic research is given the value of one when sources of information from universities/higher education or government laboratories are given a score greater than or equal to two (both on a five point Likert scale). These cut-off values correspond roughly to the median responses. Prior to estimation, the data were cleaned for outliers and missing values.

In Table 4, we present the results of applying our innovation accounting framework to the comparison of the innovation performance of seven European countries, in the same format as we did in Table 3 for the comparison of innovation performance of French manufacturing industries. Here the reference point is the innovation intensity of the hypothetical European average country, constructed as the simple average of country averages(each country being given equal weight). The "average" rows in the two panels are thus the simple averages of country-specific deviations with respect to this European average.

Again, we clearly note a lower intensity of innovation for low-R&D sectors than for high-R&D sectors. However, the inter-country differences within the two groups of sectors tend to be wider than what we observed for the inter-industry differences in French manufacturing. The size/group variable again dominates all the structural effects. Innovativeness varies in about in the same range as the sum of "structural" effects in the high-R&D sectors, but not in the low-R&D sectors where it is always much greater.

The biggest observed difference in innovation intensity is between Germany and Italy, of 18.2%in the high-R&D sectors and 27.3% in the low-R&D sectors, in favour of Germany. However, the difference in expected innovation intensity in the high-R&D sectors is only 5.5% of which 1.7% can be explained by industry composition, 1.8% by R&D effects and 3.4% by environment effects (differences in competition and proximity to basic research). The difference in expected innovation intensity is even smaller in the low-R&D sectors, of 2.1%, of which 0.8% correspond to R&D effects and 1.2% to environment effects. It is thus the case that the difference in innovativeness accounts for the bulk of the observed differences in the innovation intensity between these two countries. And of course the sources of such large difference in innovativeness remain to be understood.

V. DISCUSSION OF THE INNOVATION INDICATORS

Innovation surveys serve to increase our understanding of the innovation process. Two important pieces of information contained in these surveys are the proportion of innovative firms by sector or country and the percentage of innovative products in sales. These variables complement traditional measures of innovation, based on R&D, patents or publications. In particular, the share of innovative products in sales provides a direct measure of an innovation output and gives greater weight to successful innovations, *i.e.* those accepted by the market. There is no need to rely on additional pieces of information in order to attribute more weight to important innovations, as would be necessary in the case of patents application, such as renewal fees, forward citations, number of claims, number of parallel patents, or litigation expenses incurred (Lanjouw and Schankerman, 1999).

However, the point here is not to argue in favour of innovation-survey-based indicators over R&D, patent or bibliometric data (Brouwer and Kleinknecht; 1996;Mohnen and Dagenais, 2001, for a more detailed discussion comparing various innovation indicators). The point of this article is to demonstrate the usefulness of going beyond descriptive statistics towards model-based innovation indicators to gain a better understanding of differences in innovation performance. We propose two constructed indicators that combine information on the propensity to innovate and the intensity of innovation for innovating firms: expected innovation and innovativeness. The former corresponds to the share in sales of innovative products accounted for by variables such as size, R&D effort, closeness to basic research or competition, while the latter measures the residual share of innovative sales not accounted for by these explanatory variables. In other words, we propose an innovation accounting framework similar to the familiar growth accounting framework, where innovativeness plays a role comparable to that of TFP.

These indicators, however, require some caveats. First, the share of innovative sales refers essentially to product innovations. Looking at the data, it appears that most product innovators also declare themselves to be process innovators. The two innovations are thus largely confounded and the share in innovative sales reflects, in part, the rewards from the introduction of new processes. Second, how do we define an innovation? It is not only a question of what constitutes an innovation, which in itself is debatable and subject to the respondent's appreciation, but also a question of relying on one notion rather than on another: should we consider the notion of products new to the enterprise but not to the industry, the notion of products new to the industry or else that of products that are in the initial phase of their product life cycle? Third, it will be important for a sound comparison of innovation across space and time to have as much homogeneity as possible in the survey questionnaire. Efforts are under way to ensure greater harmonisation of the innovation surveys. If some questions are neglected in one survey, the analysis we prone in this article will be handicapped because some explanatory variables are absent for one country. In this respect, it will be useful also to ask more questions to non-innovating firms in order to gain a better understanding of the reasons why they do not innovate (using perhaps a different version of the questionnaire with a specific set of questions for such firms, or preferably by including a larger set of questions common to the two groups of firms).[16]

In this article, which we view mainly as an exercise in measurement, we have tried to make good use of the qualitative and quantitative data contained in the innovation surveys. Although the first results and insights gained are rewarding, the analysis would need to be generalised in various dimensions. More systematic sensitivity analyses would be useful. In particular, it would be interesting to compare the innovation indicators obtained using a given country or industry's innovation structure instead of estimating a common structure by pooling data. Mohnen and Dagenais (2001) find that the predicted innovation measure for Ireland and Denmark is similar regardless of whether the econometric structure used to perform the country comparison is the Danish or the Irish one. It would be also useful to analyse in more detail the sources of some of the econometric difficulties we encountered in estimating the generalised tobit specification. Beyond such analyses, it would, of course, be useful to combine innovation surveys with other survey data in order to increase the number of relevant explanatory variables to our model as it stands here and to be able to contrast indicators of R&D, patents, commercial innovations, publications, etc. Another promising line of research would be to extend the model (by adding more equations) in order to be able to analyse jointly, and hopefully better, the relations between R&D, innovation, productivity and other dimensions of firm performances (see Crépon, Mairesse and Duguet, 1998, for a step in this direction).

Finally, we wish to conclude this article by bringing to the fore the confirmation that the micro-aggregation procedure used by Eurostat to protect the statistical confidentiality in the data does not seem to significantly affect the results arising from a relatively sophisticated analysis of the kind conducted in this article, where in particular the estimated equations of interest are highly non-linear. We can thus hope that this procedure will be largely developed and will be an important contribution to the diffusion of micro level information for research purposes, and hence to its progress.

NOTES

* *The authors would like to thank Dominique Guellec for encouragements and comments and Bronwyn Hall for helpful advice. We are grateful to both SESSI and Eurostat for permission to use the individual and micro-aggregated CIS2 data for France, and again to Eurostat for permission to use the micro-aggregated CIS1 data for different European countries. This study has benefited from financial support by the OECD and CNRS.

1. It does so only with the explicit and specific consent of the countries and under some other conditions.

2. The micro-aggregation process adopted by Eurostat for CIS1 and CIS2 and its justification are explained in detail in Eurostat (1996, 1999).

3. Since what is most generally known is the number of patents not their value, the innovative sales variable has also the practical advantage of being continuous (rather than a count data variable).

4. We thus adopt the widest definition, although it would, of course, be interesting to consider and take advantage of the distinctions between new and improved products and between products new to the firm and new to the market.

5. There are, in principle, two categories of reasons to explain why we do not have the same information for the two types of firms: either a given information is only meaningful for innovating firms (the question is not posed to non-innovating firms because it makes no sense to ask them); or it is not collected because of the design of

the questionnaire (the question is not posed to non-innovating firms but it could be asked with a different questionnaire). For example, most of the questions concerning the sources or objectives of innovation fall into the first category, while the questions concerning R&D expenditures and its modalities fall into the second one (these questions make sense for the two types of firms, even if we can expect that most non-innovating firms do not perform R&D, while most R&D-performing firms are innovators). In practice, however, the reasons why many questions are restricted to innovating firms are not straightforward and fall more or less into the two categories (it is conceivable and it would be interesting to ask such questions of non-innovating firms, but it is probable that they would have particular difficulties in understanding and answering them).

6. A related option would be to consider that the same model specification will apply to both non-innovating and innovating firms. In this case, the variables which are not available for the non-innovating firms will be treated as missing variables, and the share of innovative sales of non-innovating firms will be simply taken as being zero (or a very small but unknown value to be estimated jointly with the other parameters of the model). This approach is, however, *a priori* less satisfactory, and might be impossible to implement in practice. For an example in the context of an econometric analysis of the productivity of R&D (for a sample of R&D- and non-R&D-performing French manufacturing firms) where this approach worked fairly well, see Cuneo and Mairesse (1985).

7. It also opens up the possibility of counterfactual comparison with respect to a country, an industry or a group of firms of reference (with hypothetical characteristics).

8. The analogy is direct when TFP is estimated on the basis of an econometrically estimated explicit production function; it is not as straightforward when TFP is measured on the basis of an overall weighted index of the measured factors of production, where the weights are taken to be equal to the corresponding factor shares (in total revenue or total cost) available from the firms accounts. In practice, it

is impossible to measure innovativeness based on a similar overall index of the factors of innovation for lack of external measures of appropriate weights (and of a theory of how, and under which hypotheses, they could be defined and measured). In theory, that could be conceivable (and the analogy with TFP could then be complete) if we had well-functioning markets for innovation and factors of innovation where relative prices and marginal productivities would tend to become equal.

9. See Caves, Christensen and Diewert (1982) for a rigorous generalisation of TFP in the context of interspatial productivity comparisons.

10. The SCESS, the statistical office of the Ministry of Agriculture, (not the SESSI) collected the French CIS2 data for the food sector. We have excluded the food sector from our analysis.

11. More precisely, we do not take as the dependent variable of the second equation the share of innovative sales itself, say y_2, which is limited to the 0 to 1 interval, but the logit-transformed share of innovative sales, that is $z_2 = \log (y_2/(1-y_2))$ which is unbounded. However, the logit transformation is undefined for the innovating firms declaring that none of their sales are innovative sales or on the contrary that all of their sales are innovative sales. For these firms, we replaced shares equal to 0 by 0.01 and shares equal to 1 by 0.99. We have verified that taking somewhat different values for these extreme shares does not affect our estimates in practice.

12. The standard error for the test of comparison of the sample means for the two type of samples is calculated as the average of the individual and micro-aggregated sample standard deviations (which are usually quite close) divided by square root of the common size of these samples (i.e. $\sqrt{1000}$). Note that we do the test as if the individual and micro-aggregated firms in these samples were the same, (which can only be the case for a fraction of them, since they are randomly drawn from a larger population); if we were to assume that they were all different, it will be more appropriate to multiply the standard error calculated as above by $\sqrt{2}$, and the test of comparison will thus be less stringent.

13. The difficulties we experienced in estimating ρ seem to be rather typical of the generalised tobit model. They are sometimes ignored when the likelihood function has not a unique (absolute) maximum but several local maxima, if the software program used converges to one of the local maximum (without searching for the others). However, it is reasonable to think that these difficulties are not only technical. They also reflect the fact that the specification of the model leaves something to be desired, if only for lack of more explanatory variables (and particularly so for the probit equation).

14. If our model was linear, relative innovativeness would be nothing but the industry dummy effect. However, since it is non-linear, relative innovativeness as computed also captures the linear approximation error. We have found, however, that for most industries, the linear approximation error remains small compared to the industry dummy effect.

15. In the estimation on French CIS2 data (in Section III), we make a slightly different assumption. There, a firm which declares itself to be innovative, but which gives a zero response to the percentage of innovative sales, is classified among innovating firms with a share of innovative sales taken to be 0.01. However, as previously, we take as the dependent variable of the second equation the logit-transformed share of innovative sales (and replace shares equal to 1 by 0.99).

16. See endnote 5 above.

Annex

INDUSTRY DEFINITIONS

Industry	NACE code (Rev. 1)	Industry definition
		High-R&D sectors
Vehicles	34-35	Manufacture of motor vehicles, trailers, semi-trailers, and other transport equipment
Chemicals	23-24	Manufacture of coke, refined petroleum products and nuclear fuel, manufacture of chemicals and chemical products
Machinery	29	Manufacture of machinery and equipment nec
Electrical	30-33	Manufacture of office machinery and computers, electrical machinery and apparatus, radio, television and communication equipment and apparatus, medical, precision and optical instruments, watches and clocks
		Low-R&D sectors
Food*	15-16	Manufacture of food, beverages and tobacco
Textiles	17-19	Manufacture of textiles, wearing apparel, dressing and dyeing of fur, tanning, and dressing of leather, luggage, handbags, saddlery, harness and footwear

Wood	20-22	Manufacture of wood and products of wood and cork, except furniture, manufacture of straw and plaiting materials, pulp, paper, and paper products, publishing, printing, and reproduction of recorded media
Plastics, rubber	25	Manufacture of rubber and plastic products
Non-metallic	26	Manufacture of other non-metallic mineral products
Basic metals	27-28	Manufacture of basic metals, fabricated metal products, except machinery and equipment
NEC	36	Manufacture of furniture, manufacturing nec

*The food industry is excluded from our analysis of the French data in section III.

REFERENCES

Archibuggi, D., P. Cohendet, A. Kristensen and K.A. Schäffer (1994), *Evaluation of the Community Innovation Survey (CIS), Phase I*, EIMS Publication No. 11, IKE Group, Department of Business Studies, Aalborg, Denmark.

Brouwer, E. and A. Kleinknecht (1996), "Determinants of Innovation: A Micro-econometric Analysis of Three Alternative Output Indicators", in A. Kleinknecht (ed.), *Determinants of Innovation: The Message from New Indicators*, Macmillan Press, London.

Caves, D., L. Christensen and E. Diewert (1982), "Multilateral Comparisons of Output, Input, and Productivity using Superlative Index Numbers", *Economic Journal* 92, pp. 1393-1414.

Crépon, B., E. Duguet and J. Mairesse (1998), "Research and Development, Innovation and Productivity: An Econometric Analysis at the Firm Level", *Economics of Innovation and New Technology*, Vol. 7, No. 2, pp. 115-158.

Cunéo, Ph. et J. Mairesse (1985), "Recherche-développement et performances des entreprises", *Revue Economique*, numéro spécial sur l'Économie de la recherche-développement, Vol. 36, No. 4, pp. 1001-1041

Eurostat (1996), *Manual on Disclosure Control Methods. 9E,* Statistical Office of the European Communities, Luxembourg.

Eurostat (1999), "Annex II.9. Micro-Aggregation Process", in *The Second Community Innovation Survey*, Statistical Office of the European Communities, Luxembourg.

Eurostat, (1997), *The Community Innovation Survey*, CD-Rom, Statistical Office of the European Communities, Luxembourg.

Griliches, Z. and J. Mairesse (1984), "Productivity and R&D at the Firm Level", in Z. Griliches (ed.), *R&D, Patents and Productivity*, University of Chicago Press, Chicago.

Hu, X. and C. DeBresson (1998), "An Empirical Evaluation of the Eurostat Micro-aggregation Procedure for the Analysis of the Community Innovation Survey", technical report, mimeo.

Lanjouw, J. and M. Schankerman (1999), "The Quality of Ideas: Measuring Innovation with Multiple Indicators", NBER Working Paper No. 7345, Cambridge, Mass.

Mohnen, P. and M. Dagenais (2001), "Towards an Innovation Intensity Index. The Case of CIS-1 in Denmark and Ireland", in A. Kleinknecht and P. Mohnen (eds.), *Innovation and Firm Performance. Econometric Explorations of Survey Data*, Palgrave, London (forthcoming).

Mohnen, P., J. Mairesse and M. Dagenais (2001), "The Importance of Being Innovative: A Comparison across Seven European Countries", mimeo.

OECD (1963), *The Measurement of Scientific and Technical Activities – Frascati Manual*, OECD, Paris.

OECD (1992), "OECD Proposed Guidelines for Collecting and Interpreting Technological Innovation Data – Oslo Manual", first edition, OECD, Paris.

OECD and Eurostat (1997), *OECD Proposed Guidelines for Collecting and Interpreting Technological Innovation Data – Oslo Manual*, second edition, OECD, Paris.

Table 1. **Summary statistics: CIS2 data for France**

Individual data from SESSI and micro-aggregated data from Eurostat
"high-R&D" and "low-R&D" sectors

Variable	High-R&D sectors		Low-R&D sectors	
Type of data	Individual data	Micro-aggregated data	Individual data	Micro-aggregated data
Number of firms	1 000	1 000	1 000	1 000
% of firms in vehicles	15.6	14.3	-	-
% of firms in chemical	22.7	24.2	-	-
% of firms in M&E	29.4	29.4	-	-
% of firms in electrical	32.3	32.1	-	-
% of firms in textile	-	-	22.6	19.8
% of firms in wood	-	-	20.4	20.7
% of firms in plastic	-	-	9.3	10.7
% of firms in non-metal.	-	-	8.6	8.8
% of firms in metals	-	-	31.1	31.3
% of firms in nec	-	-	8.0	8.7
Average number of employees (in logs)	5.21	5.18	4.51	4.56
	(0.05)	(0.05)	(0.04)	(0.04)
	[1.46]	[1.46]	[1.20]	[1.21]
% of firms belonging to a group	69.4	67.8	45.8	49.2
	(1.47)	(1.47)	(1.58)	(1.58)
	[46.1]	[46.8]	[49.9]	[50.0]
Percentage of innovators	75.0	76.1	48.2	45.9
	(1.36)	(1.36)	(1.56)	(1.56)
	[43.3]	[42.7]	[50.0]	[49.9]
Share in sales of innovative products, for innovators (y2)	28.4	27.8	23.3*	21.2*
	(0.86)	(0.86)	(0.84)	(0.84)
	[27.2]	[27.4]	[28.5]	[24.8]
Log of y2/(1-y2), trimmed	-1.38	-1.40	-1.83*	-1.97*
	(0.06)	(0.06)	(0.07	(0.07)
	[2.0]	[2.1]	[2.5])	[2.1]
% of R&D firms among innovators	83.9*	76.0*	56.9*	49.9*
	(1.26)	(1.26)	(1.58)	(1.58)
	[36.8]	[42.8]	[49.6]	[50.1]
Average R&D/sales in %, if performing R&D	4.6	4.8	1.8*	2.4*
	(0.19)	(0.19)	(0.08)	(0.08)
	[6.0]	[5.7]	[2.4]	[2.5]
% of continuous R&D, if performing R&D	80.0*	84.1*	67.9*	74.2*
	(1.21)	(1.21)	(1.43)	(1.43)
	[40.1]	[36.6]	[46.8]	[43.8]
% of co-operating firms among innovators	52.7	52.7	33.4	34.4
	(1.58)	(1.58)	(1.50)	(1.50)
	[50.0]	[50.0]	[47.2]	[47.6]
% of strongly perceived competition among innovators	68.0	66.0	54.8	57.1
	(1.49)	(1.49)	(1.57)	(1.57)
	[46.7]	[47.4]	[49.8]	[49.6]
% of close proximity to basic research among innovators	25.7	26.3	15.6*	13.1*
	(1.39)	(1.39)	(1.11)	(1.11)
	[43.8]	[44.1]	[36.3]	[33.8]

Note: The first figures in each cell are the sample means, while those in brackets are the sample standard deviations. The figures in parentheses are the standard errors of the tests of comparison of the sample means for the individual and micro-aggregated data samples (computed as the average of two corresponding standard deviations divided by the square root of 1000). The superscript * indicates that these sample means are significantly different at the 5% confidence level.

Table 2. **Maximum likelihood estimates of the generalised tobit model of innovation: CIS2 data for France**

Micro-aggregated data from Eurostat and individual data from SESSI

High-R&D sectors

Variables	Micro-aggregated data: Propensity to innovate	Micro-aggregated data: Intensity of innovation	Individual data: Propensity to innovate	Individual data: Intensity of innovation
Vehicles	0.51* (.13)	-3.33* (.33)	0.44* (.12)	-3.45* (.30)
Chemicals	0.63* (.12)	-3.71* (.32)	0.40* (.12)	-3.66* (.30)
Machinery and equipment	0.82* (.11)	-2.82* (.29)	0.66* (.11)	-2.75* (.28)
Electrical	0.71* (.10)	-3.03* (.30)	0.60* (.10)	-2.97* (.28)
Log-employees	0.29* (.04)	0.45* (.07)	0.24* (.04)	0.50* (.07)
Part of a group	0.15 (.11)	0.27 (.23)	0.30* (.11)	0.31 (.23)
R&D/sales	-x-	3.17*(1.42)	-x-	3.17*(1.30)
Innovators not doing R&D	-x-	-0.19 (.23)	-x-	-0.31 (.21)
Doing R&D on a continuous basis	-x-	0.52* (.21)	-x-	0.39* (.18)
Co-operating in innovation	-x-	0.11 (.14)	-x-	0.22 (.14)
Perceived competition	-x-	0.22 (.14)	-x-	0.10 (.14)
Proximity to basic research	-x-	-0.02 (.16)	-x-	-0.13 (.16)
Standard error of error terms	1 (assumed)	2.47* (.07)	1 (assumed)	2.45*(.07)
Correlation coefficient of the two error terms	0.95 (imposed)		0.95 (imposed)	

Low-R&D sectors

Variables	Micro-aggregated data: Propensity to innovate	Micro-aggregated data: Intensity of innovation	Individual data: Propensity to innovate	Individual data: Intensity of innovation
Textile	-0.44* (.10)	-5.08* (.42)	-0.33* (.09)	-5.28* (.42)
Wood	-0.50* (.10)	-5.56* (.44)	-0.23* (.11)	-5.03* (.44)
Plastic and rubber	0.18 (.14)	-3.77* (.49)	0.29* (.14)	-4.09* (.51)
Non-metallic products	-0.24 (.14)	-4.61* (.54)	0.03 (.14)	-4.89* (.54)
Basic metal	-0.18* (.09)	-4.90* (.40)	-0.12 (.08)	-5.10* (.38)
NEC	0.01 (.14)	-3.19* (.51)	0.04 (.14)	-4.11* (.53)
Log-employees	0.23* (.04)	0.38* (.12)	0.23* (.04)	0.48* (.14)
Part of a group	0.28* (.10)	0.40 (.29)	0.18 (.10)	0.74* (.34)
R&D/sales	-x-	-2.64 (5.14)	-x-	8.35 (5.50)
Innovators not doing R&D	-x-	-0.66* (.31)	-x-	-0.66* (.27)
Doing R&D on a continuous basis	-x-	0.31 (.30)	-x-	-0.36 (.29)
Co-operating in innovation	-x-	0.18 (.20)	-x-	-0.05 (.22)
Perceived competition	-x-	0.37* (.17)	-x-	0.55* (.19)
Proximity to basic research	-x-	0.16 (.28)	-x-	0.30 (.29)
Standard error of error terms	1 (assumed)	3.03* (.11)	1 (assumed)	3.43* (.12)
Correlation coefficient of the two error terms	0.95 (imposed)		0.95 (imposed)	

Note: Standard errors of estimates in parentheses. The superscript * indicates a coefficient statistically different from zero at a 5% confidence level.

Table 3. **Average observed and expected innovation intensities, and innovativeness**

Ten manufacturing sectors, individual and micro-aggregated CIS2 data for France

	Average intensity: full sample	Size + group effects	R&D effects	Environment effects	Sum of structural effects	Expected intensity	Innovativeness	Observed intensity
High-R&D sectors – individual data								
Vehicles	21.3	3.6	0.1	0.0	3.7	25.0	-1.0	24.0
Chemicals	21.3	1.3	0.4	0.0	1.7	23.0	-6.7	16.3
Machinery &equipment	21.3	-2.5	-0.6	0.0	-3.0	18.3	2.2	20.5
Electrical products	21.3	-0.6	0.2	0.0	-0.4	20.9	3.3	24.2
Average	21.3	0.0	0.0	0.0	0.0	21.3	0.0	21.3
Low-R&D sectors – individual data								
Textiles	11.2	-0.5	0.1	-0.3	-0.7	10.5	-1.5	9.1
Wood	11.2	0.1	-0.3	-0.2	-0.4	10.9	-0.4	10.5
Plastics, rubber	11.2	2.0	-0.2	0.8	2.7	13.9	1.7	15.6
Non-metallic mineral products	11.2	1.8	-0.1	0.8	2.5	13.7	-3.0	10.7
Basic metals	11.2	-0.4	0.2	0.0	-0.2	11.1	-0.5	10.6
NEC	11.2	-0.3	-0.1	0.0	-0.4	10.8	6.5	17.4
Average	11.2	0.0	0.0	0.0	0.0	11.2	0.0	11.2
High-R&D sectors – micro-aggregated data								
Vehicles	21.1	2.0	-0.3	0.0	1.7	22.8	1.2	24.0
Chemicals	21.1	1.3	0.4	0.0	1.7	22.9	-6.9	16.0
Machinery & equipment	21.1	-1.8	-0.8	0.0	-2.6	18.5	2.4	20.9
Electrical products	21.1	-0.4	0.5	0.0	0.1	21.3	2.7	24.0
Average	21.1	0.0	0.0	0.0	0.0	21.1	0.0	21.1
Low-R&D sectors – micro-aggregated data								
Textiles	9.7	-0.4	0.0	-0.1	-0.5	9.2	-1.7	7.5
Wood	9.7	0.0	-0.1	-0.1	-0.2	9.5	-2.7	6.8
Plastics, rubber	9.7	1.5	0.0	0.5	2.0	11.7	2.7	14.4
Non-metallic mineral products	9.7	0.6	0.3	0.2	1.2	10.9	-1.4	9.5
Basic metals	9.7	-0.3	0.1	0.0	-0.2	9.5	-0.7	8.8
NEC	9.7	0.7	-0.5	0.1	0.3	10.0	9.7	19.7
Average	9.7	0.0	0.0	0.0	0.0	9.7	0.0	9.7

Table 4. **Average observed and expected innovation intensities, and innovativeness**
Seven European countries, micro-aggregated CIS1 data from Eurostat

	European intensity	Industry effect	Size + group effects	R&D effects	Environment effects	Sum of structural effects	Expected intensity	Innovative-ness	Observed intensity
					High-R&D sectors				
Belgium	34.7	-1.2	2.6	0.9	0.7	3.0	37.7	0.2	37.9
Denmark	34.7	1.3	-0.7	0.4	0.4	1.4	36.1	0.7	36.8
Germany	34.7	1.3	0.6	0.9	1.7	4.5	39.2	4.6	43.8
Ireland	34.7	-0.6	-2.2	0.1	-0.1	-2.6	32.1	3.1	35.2
Italy	34.7	0.4	1.1	-0.9	-1.6	-1.0	33.7	-8.1	25.6
Netherlands	34.7	-0.8	-1.1	-0.6	0.1	-2.4	32.3	1.0	33.3
Norway	34.7	-0.5	-0.2	-0.7	-1.5	-2.9	31.8	-1.6	30.2
Average	34.7	0.0	0.0	0.0	0.0	0.0	34.7	0.0	34.7
					Low-R&D sectors				
Belgium	22.3	0.4	0.3	0.2	0.1	1.0	23.3	5.5	28.8
Denmark	22.3	0.0	0.7	0.0	-0.1	0.6	22.9	-2.7	20.2
Germany	22.3	0.3	0.4	0.4	0.6	1.7	24.0	13.5	37.5
Ireland	22.3	0.4	-0.9	0.2	0.2	-0.1	22.2	3.3	25.5
Italy	22.3	0.7	-0.1	-0.4	-0.6	-0.4	21.9	-11.7	10.2
Netherlands	22.3	-1.0	-0.2	-0.2	-0.1	-1.5	20.8	-2.4	18.4
Norway	22.3	-0.8	-0.2	-0.1	-0.2	-1.3	21.0	-5.4	15.6
Average	22.3	0.0	0.0	0.0	0.0	0.0	22.3	0.0	22.3

Note: Small discrepancies are due to rounding errors.

Figure 1. **Histogram of the share of innovative sales for the sub-sample of innovative firms in the high-R&D sector samples**

Individual data from SESSI and micro-aggregated data from Eurostat

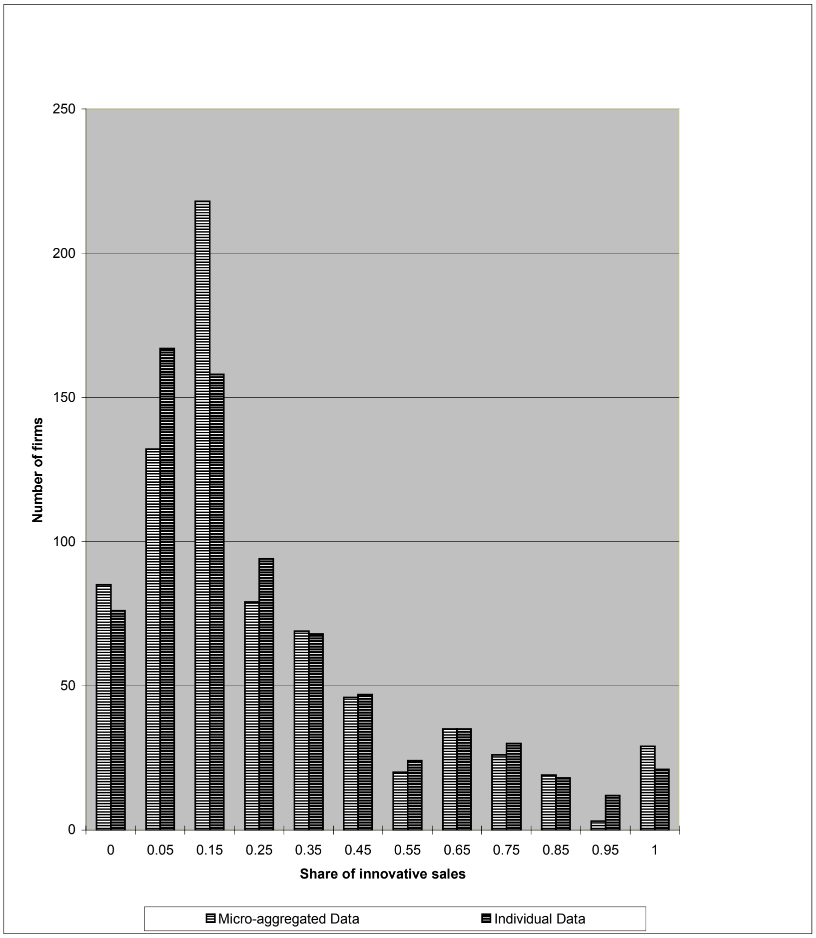

Figure 2. **Histogram of the share of innovative sales for the sub-sample of innovative firms in the low-R&D sector samples**

Individual data from SESSI and micro-aggregated data from Eurostat

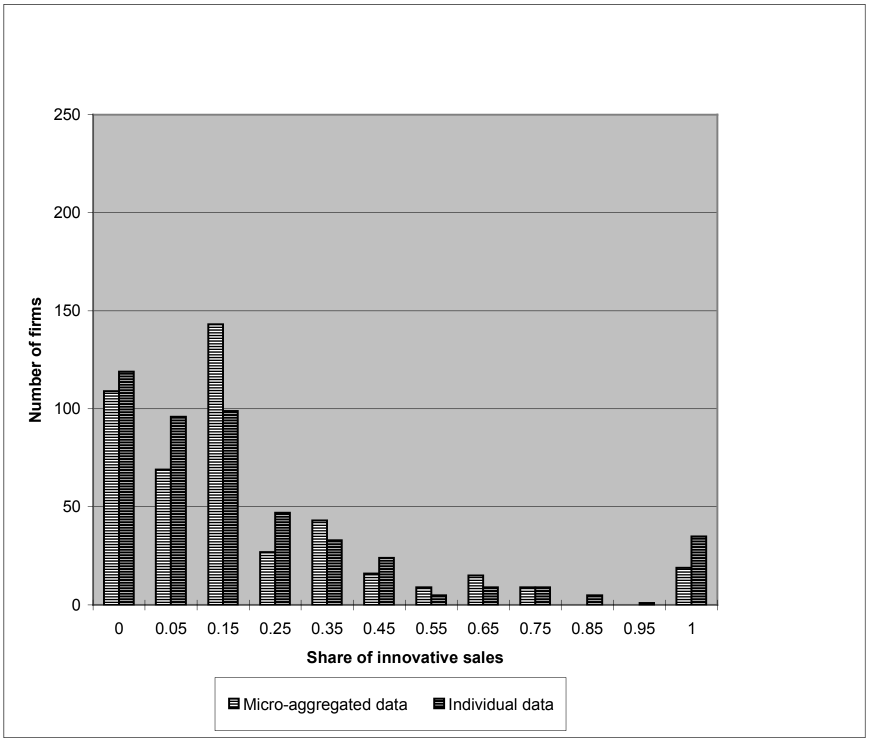

Figure 3. **"Structural effects" and innovativeness in the high-R&D sector samples**

Individual data from SESSI and micro-aggregated data from Eurostat

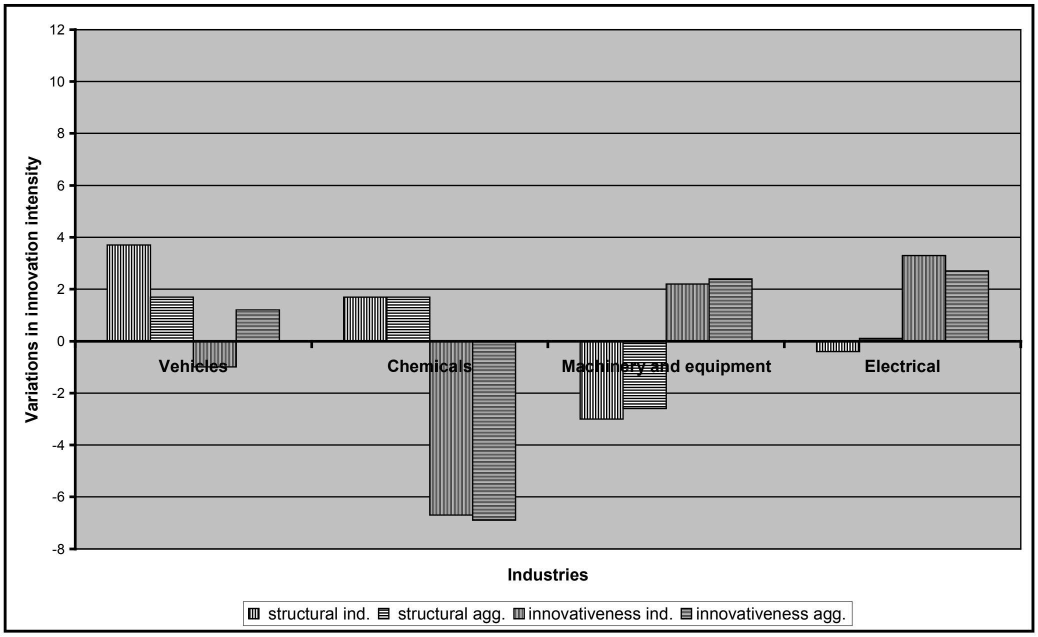

Figure 4. **"Structural effects" and innovativeness in the low-R&D sector samples**

Individual data from SESSI and micro-aggregated data from Eurostat